

Project:	1.1.1.1 Vehicle Mileage Based User Fee Study, Phase III
Work Order No./Contract Date:	UNR Subaward Number: UNR-14-10
Reporting Period:	June 2014
Scheduled Project Duration:	16 Months (Sept. '13 - Dec. '14)
Actual / Expected Project Duration:	16 Months
Project Start Date:	07 September 2013
Team Management	
Client	Project Team Leader
Nevada Department of Transportation (NDOT) Contact Person: Alauddin Khan, MBA, P.E., PTOE. Chief Performance Analysis Engineer Nevada Department of Transportation 1263 Stewart Street, Carson City NV 775-888-7192	Shunfeng Song, Ph.D. http://www.unr.edu/business/people/economics-faculty/shunfeng-song Professor of Economics University of Nevada, Reno 1664 N Virginia St, Reno, NV 89557 Office: AB 318A; Ph# (775) 784-6860 Email: song@unr.edu
Scope	Comments
Have the objectives changed?	No
Has the deliverable scope changed?	No
Has the logical scope changed	No
Has the financial scope changed?	No
Has the Core Team Changed?	No

Delivery Schedule	
Is the project being impacted by external factors?	No
Will the estimated project finish date be missed?	No
Are there review and approval problems?	No

1.1.1.2 Key Deliverables/Reports Till Date and Status

Sl. No.	Deliverable Name covering the scope of work	Submission Status (Submitted/In-process/ Not Due)	Approval Status (Approved / Pending / NA)
1.			
2.			
3.			

1.1.1.3 Major Activities till the reporting period (June '14)

- Literature Review of Equity Impacts of VMT Fee
- Data Collection
- Estimation of Discrete Choice Models
- Corrections for Selection Bias and Endogeneity in Mileage Demand Estimations
- Annual Impacts on Different Demographics

Summary of the Research Work

Analysis of the impact of switching from a gasoline tax to a tax per mile of driving in order to insure the sustainability of the National Highway Transportation Fund. This depends critically on the demand response of highway users in response to the change. Unfortunately, there are multiple sources of statistical bias when estimating this type of model, which require the use of advanced econometric techniques. Once these are adjusted for, impacts on various segments of the population are analyzed.

Administration Points/Issues, including Pending Invoices

--

1.1.1.4 Plan for the Next Quarter

1. Markov Chain Monte Carlo estimations of alternative model structures for robustness.
2. Time Series analysis of a panel of states to determine differences in revenue changes that may result based on demographic and geographical factors.

Equity Concerns in Infrastructure Financing: The Gas Tax vs. Vehicle Miles Traveled Fees

Nathan Wiseman

Ph.D. Candidate

Department of Economics

University of Nevada

Reno, NV 89557 USA

Tel: (530) 524-4752

Fax: (775) 784-4728

Email: nwiseman@unr.edu

Shunfeng Song

Professor

Department of Economics

University of Nevada

Reno, NV 89557 USA

Tel: (775) 784-6860

Fax: (775) 784-4728

Email: song@unr.edu



University of Nevada, Reno
Statewide • Worldwide

EXECUTIVE SUMMARY

The gasoline tax, which accounts for about 92.5% of revenue used for highway maintenance and improvements, is an unsustainable source of revenue for several reasons:

1. It has not been raised since 1993, and is not indexed to inflation, so the amount that drivers pay per mile in real terms has declined over time.
2. The cost of maintaining and improving infrastructure has increased at a rate surpassing that of inflation alone.
3. Increasing fuel efficiency of the nation's vehicle fleet, including alternative fuel and electric vehicles, leads to less tax paid per mile driven and inequitable differences in the amount paid by different motorists even though they cause the same amount of damage to roadways.

A potential solution to the problem is to begin levying taxes on miles driven rather than gallons of gasoline consumed. Several states are presently studying the feasibility of such an approach. Previous stages of the present study included the design of a mechanism to administer a mileage fee system, public outreach, evaluation of privacy concerns, and economic analysis of the equitability of a mileage based fee.

Previous studies have found mixed results with respect to equity when comparing the current system with a mileage fee. One possible reason is the failure to control for the endogeneity¹ of vehicle choice in the estimation of demand for miles, which can cause inconsistent and biased

¹ Endogeneity occurs when the error term of a regression is correlated with one of the explanatory variables. This is due to some sort of feedback between the independent and dependent variables. For example, if the amount of miles that people drive depends on the cost of driving, but people who drive more also tend to purchase vehicles with lower operating costs (each can cause the other), the cost of driving is said to be endogenous with miles driven. This violates the assumptions of traditional statistical models based on ordinary least squares (OLS).

estimates. This report utilizes established econometric methods (Dubin & McFadden, 1984) to correct for selection bias and vehicle choice endogeneity, and looks in more depth at equity concerns with respect to income, rural and urban households, and households with retirees.

The main findings of the present research are as follows:

1. Both the fuel tax and a mileage based fee are regressive, meaning those with lower incomes pay more tax as a percentage of their income.
2. While the absolute difference (fuel tax – mileage fee) is small on average, data from the 2009 National Highway Transportation Survey (NHTS) suggests that a mileage fee would be slightly less regressive.
3. There is considerable variation within income groups, with some households benefitting and others not. The 2009 NHTS suggests that the proportion of households benefitting from a switch to a mileage fee would decrease with household income. The amount of variation also increases with household income.
4. The median household would see a \$5 increase in annual consumer surplus. About 25% of households would lose in excess of \$25 in annual consumer surplus. Of these households, the average loss in consumer surplus would be about \$125. About 25% of households would gain in excess of \$45 in annual consumer surplus. Of these households, the average gain would be about \$88. A significant number of households with incomes over \$25K would gain or lose in excess of \$200.
5. Rural households and urban households with retired persons would benefit, on average, at the expense of urban households without retirees. Rural households would see the largest range in impacts, while households with retirees would see the smallest.
6. High mileage drivers (those driving in excess of 25K miles per year) would pay more under a mileage fee system than under the gas tax, while all other drivers would pay less on average.

Summary of Main Results with Respect to Income

Income	Gas Tax/Income	Revenue Neutral VMT Fee/Income	Change in Consumer Surplus (\$/HH)	Change in CS/Income	% of HH benefitting	95% Between (\$/HH)	
						Loss of	Gain of
\$5,000 to \$24,999	1.377%	1.359%	2.51	0.0158%	60%	-174.14	179.16
\$25,000 to \$49,999	0.742%	0.741%	0.46	0.0017%	58%	-247.34	248.26
\$50,000 to \$74,999	0.589%	0.590%	-0.76	-0.0010%	56%	-264.14	262.62
\$75,000 to \$99,999	0.492%	0.495%	-2.42	-0.0027%	55%	-300.72	295.88
More than \$100,000	0.417%	0.420%	-3.11	-0.0028%	56%	-320.91	314.69

Equity with respect to income should not be a major obstacle in the implementation of a mileage based fee to fund highway maintenance and improvements. How a switch to a VMT fee would affect a given household depends mainly on the fuel economy of their vehicle and how much they drive. Those with higher incomes tend to drive newer vehicles and more miles. The 1990s saw declining fuel efficiency in new vehicles, which is likely the reason that previous studies indicated that higher income households would benefit the most from a change. With recent increases in fuel efficiency and corporate average fuel economy (CAFE) standards set to improve new vehicle fuel efficiency drastically over the next decade, it is likely that a VMT fee system will become increasingly progressive relative to the gas tax.

Summary of Consumer Surplus Change based on Location and Whether Retired (\$/HH)

Household Income	Rural			Urban		
	Retired	Working	Total	Retired	Working	Total
\$5,000 to \$24,999	7.27	-2.52	3.47	5.38	-2.87	-2.04
\$25,000 to \$49,999	9.80	-4.31	2.74	3.48	-4.85	-0.60
\$50,000 to \$74,999	8.88	-4.94	-0.34	6.86	-5.38	-0.96
\$75,000 to \$99,999	12.44	-2.54	1.07	4.01	-6.74	-3.93
More than \$100,000	3.92	-3.87	-2.28	6.40	-5.76	-3.39

Another potential area of concern is whether a VMT fee system would adversely affect rural areas or households with retired persons. The results of this study are consistent with previous

research which suggests that on average rural households and retired persons would benefit. This is likely due to the lower average fuel economy in rural areas (due to more trucks) and the fact that retired persons are likely to own older vehicles.

Summary of the Range of Change in Consumer Surplus

Income	Rural Retired		Rural Working		Urban Retired		Urban Working	
	95% Between (\$/HH)		95% Between (\$/HH)		95% Between (\$/HH)		95% Between (\$/HH)	
	Loss of	Gain of	Loss of	Gain of	Loss of	Gain of	Loss of	Gain of
\$5,000 to \$24,999	-156.31	170.85	-275.84	270.80	-116.76	128.00	-197.11	191.37
\$25,000 to \$49,999	-201.42	221.02	-379.73	371.11	-185.57	193.27	-245.28	235.56
\$50,000 to \$74,999	-244.24	262.00	-373.60	363.72	-162.23	176.89	-252.88	242.12
\$75,000 to \$99,999	-245.94	270.82	-381.23	376.17	-213.95	223.05	-293.88	280.40
More than \$100,000	-317.20	325.04	-422.35	414.61	-212.69	226.75	-302.74	291.22

While households in rural areas, particularly those with retired persons, would tend to pay slightly less on average under a VMT fee system, the range of impacts would be larger in rural areas. Among households without retirees, almost all households in urban areas would see a change in annual consumer surplus of less than \$300, with most of the lowest income households seeing a change of less than \$200. A significant number of households in rural areas could expect to see impacts between \$300 and \$400 dollars, with some higher income households seeing a change in annual consumer surplus in excess of \$400. Households with retirees would see a significantly smaller range of impacts, particularly in urban areas.

Summary of Distributional Effects Based on Miles Driven

Total Household Miles (Annual)	Gas Tax/Income	Revenue Neutral VMT Fee/Income	Average Change in Consumer Surplus		Average Number of Vehicles Per Household	95% Between (\$/HH)	
			Surplus (\$/HH)	% of HH benefitting		Loss of	Gain of
Less Than 7,500	0.32%	0.29%	9.08	68%	1.3	-38.62	56.78
7,500 to 14,999	0.58%	0.55%	10.30	57%	1.6	-99.56	120.16
15,000 to 24,999	0.70%	0.69%	6.25	55%	2.0	-174.09	186.59
25,000 or More	1.17%	1.22%	-25.49	49%	2.6	-489.65	438.67

Those who drive the most miles would tend to pay more on average. These households tend to have higher incomes and own more vehicles, although there are some exceptions. Overall, a

VMT fee would be more progressive with respect to miles driven, meaning households who drive in excess of 25K miles per year would tend to pay a larger share of their income in tax relative to households driving less. The annual miles driven by a household, combined with the fuel efficiency of their vehicles are the fundamental determinants of the extent to which they would be better or worse off under a VMT fee system relative to the current gasoline tax. Households with below average fuel economy would benefit from the switch relative to households with above average fuel economy, regardless of other factors. The size of this benefit or loss depends entirely on how much they drive their vehicles. Households that drive more would see a larger change in consumer surplus.

A potential drawback of the present study is that it assumes people will respond to a change in price due to a change in the tax structure the same way they respond to a change in the price of gasoline. A recent paper (30) suggests that people have a much larger response to a change in the gasoline tax than to a change in the price of gasoline, likely due to the saliency of a tax increase. Essentially, people are much more aware of the increase when it comes from a tax due to media coverage and political debate. It is likely that a change to a mileage fee would be particularly salient, as it would likely require a new form of administration, which could lead to a larger behavioral adjustment. If this is true, the range of impacts could be significantly larger than as stated in this paper.

Another potential issue is that in calculating a VMT fee that would lead to an equivalent amount of revenue it was implicitly assumed that the administration costs of a VMT fee system would be equivalent to the cost of administering the current gasoline tax. If the administration costs were more a higher fee would be required in order to obtain the same amount of revenue. While the overall pattern of impacts between households of different incomes and other demographic factors would likely remain the same as those found in this paper, a higher fee would make it so a switch would be detrimental to more households.

Table of Contents

EXECUTIVE SUMMARY	4
INTRODUCTION	10
LITERATURE REVIEW	12
Distributional Effects of a VMT Fee	12
Modeling Vehicle Choice and Usage Sequentially to Control for Endogeneity	13
DATA	16
MODEL	18
RESULTS	19
Welfare Impacts with Respect to Income and Other Demographic Factors	22
CONCLUSION	25
APPENDIX	27
REFERENCES	31

INTRODUCTION

The gasoline tax is employed as an excise tax at both the state and national level in order to provide funding for transportation infrastructure development and maintenance. For a variety of reasons, the present funding mechanism is becoming increasingly unsustainable. Due to the gasoline tax not varying with the price of gasoline nor being indexed to inflation, the amount being transferred to the National Highway Transportation Fund (NHTF) per mile driven has been decreasing in real terms steadily since the last time the tax was increased. The Government Accountability Office included funding the nation's surface transportation system as one of 30 high risk areas in its 2013 report to congress (1), where it has been included since 2007. Another factor that threatens the long term feasibility of utilizing excise taxes on gasoline as a stable funding mechanism is the increasing fuel efficiency of the nation's automobile fleet. According to the Bureau of Transportation Statistics (2), new vehicle fuel efficiency improved from 28.8 miles per gallon (MPG) in 2001 to 33.8 MPG in 2010 for passenger cars. New light trucks saw a similar increase from 20.9 MPG to 25.2 MPG over the same period. These increases are dramatic relative to the previous ten years. Continually increasing requirements from the Corporate Average Fuel Economy (CAFE) standards aim to increase fuel efficiency of passenger cars to 35.5 MPG in 2016 and 54.5 MPG in 2025. These commitments are aimed at reducing greenhouse gas emissions and dependence on foreign oil, and could save consumers money on gasoline; however, they also serve to further undermine the NHTF, as vehicles will be doing more damage to roads per gallon of gasoline consumed. Combine this with the inability of

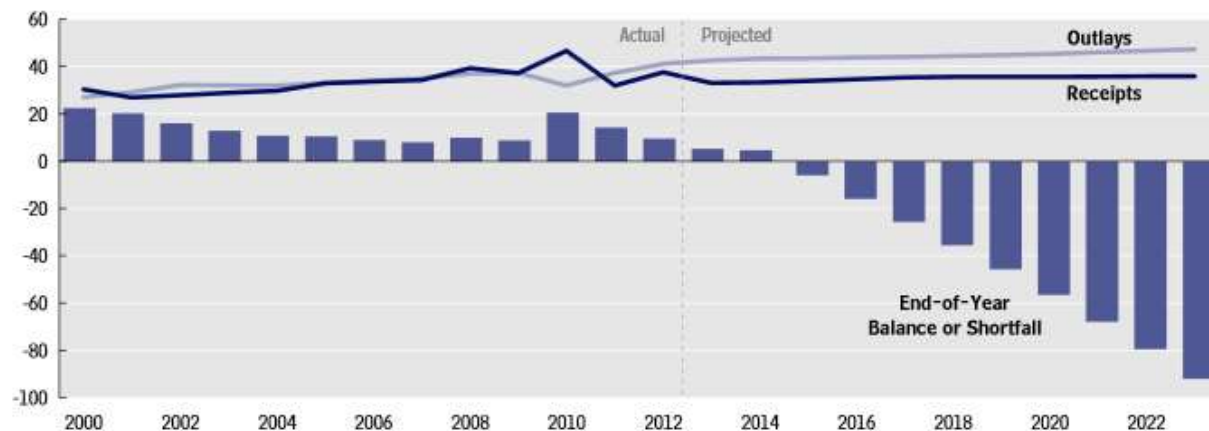
Congress to agree on a long term transportation finance bill, and the result is a desire to find alternative mechanisms to fund highway development and maintenance in the future.

According to a recent report by the Congressional Budget Office (CBO, 3), “at the end of 2012, the total obligated amounts of contract authority in the highway account were equal to about two years of collections of excise taxes.” A series of short term measures, in the form of increasingly large transfers from the general fund of the treasury, which have totaled \$44 billion since 2008, have kept the NHTF afloat. The current funding, known as Moving Ahead For Progress in the 21st Century (MAP-21, Public Law 112-141) will expire on September 30th, 2014. It is projected that the NHTF will require another \$14 billion from the general fund in 2015 to avoid a shortfall. Furthermore, all but 4.3 cents of the federal fuel tax is set to expire in 2016. Figure 1 shows the CBO’s projections, given that the federal fuel tax is renewed at the current rate of 18.4 cents per gallon, with construction costs increasing at the rate of inflation. The CBO estimates that without spending cuts, taxes on motor fuels will have to be raised by about 10 cents per gallon in order to meet current obligations.

Figure 1.

Receipts, Outlays, and Balances of the Highway Trust Fund

(Billions of dollars)



Source: Congressional Budget Office.

Note: Estimates are based on CBO's February 2013 baseline projections.

Due to the political infeasibility and potential inequity that would result from increasing the gasoline tax, many states are investigating the potential options to increase transportation funding in a way that will be more equitable. Some possible solutions include toll roads, including those run by private entities, and per mile fees, often referred to as vehicle miles traveled (VMT) fees. Schweitzer (4) provides a recent review of empirical research on the

equity implications of various transportation funding mechanisms. A recent working paper by Miller (5) looks at political implications of different funding mechanisms, arguing for the consideration of transitioning towards a decentralized VMT fee system, possibly through privatization.

The goal of this study is to provide a consistent comparison of the distributional effects of instituting a VMT fee, including tax incidence and other welfare measures. The next section reviews literature relevant to the present inquiry; section III details the model used; section IV describes the data; section V compares results to those obtained in previous studies; section VI concludes.

LITERATURE REVIEW

The focus of this review is on studies relevant to estimating the welfare effects of instituting a vehicle miles traveled (VMT) fee. While the overall impact on society is likely to be similar to the current structure (6), there could be considerable heterogeneity in how the tax burden is distributed based on income and other demographic characteristics. Since no known studies on VMT equity have controlled for selection bias or endogeneity, some related literature utilizing these techniques in similar contexts is also reviewed.

Distributional Effects of a VMT Fee

Several studies have attempted to estimate the distributional effects of various VMT fee structures, utilizing a variety of methods and measures. These studies rely on a specification that estimates the demand for miles driven in response to the price per mile. The consensus is that a VMT fee would be regressive, meaning that those with a lower income would pay a larger proportion of their income in tax under the structure than those with higher incomes; however, since most assume that a VMT fee would replace rather than supplement the current gas tax, the concern is whether a VMT fee would be *more* regressive than the current gasoline tax. Most recent studies on this issue have used the 2001 and/or 2009 National Household Transportation Survey (NHTS), with older studies more likely to use the annual Consumer Expenditure Surveys (CEX) administered by the Bureau of Labor Statistics (BLS).

Zhang et al. (7) analyzed a subset of 3,581 households from the 2001 NHTS, estimating the short-run and long-run impacts of a VMT fee. The short-run model is estimated using ordinary least squares (OLS), including a variable to indicate whether a household can substitute

between types of vehicles to drive and a variable indicating the number of vehicles owned. This model suggests that VMT is more regressive than the gasoline tax, but that rural households will benefit from the VMT structure at the expense of urban households. They find that lower income households would lose consumer surplus, while higher income households would gain it. Their long-run model appends the NHTS data with vehicle prices and weights from the 2001 *Ward's Automotive Yearbook* and the *Internet Auto Guide*, respectively. They estimate separate models for vehicle number, and vehicle combinations, using weight to classify vehicles as either cars or trucks. They do not use the results of the vehicle choice models to explicitly control for endogeneity. Their long-run results indicate that rural households will actually be worse off, although they conclude that the redistributive impact of the VMT fee structure is negligible compared to those resulting from long-run fluctuations in the price of gasoline. A subsequent study (8) used OLS and the same data, but looked at only Oregon households, and concluded that a VMT fee would be slightly more regressive than the gas tax.

Weatherford (9) used the national representation of the same data (NHTS 2001) to estimate the effects of a 0.98 cent per mile VMT fee at the national level, and found that a VMT fee structure would redistribute the tax burden from those who are retired to younger households and from rural households to urban households, while 98% of households would see a change of less than \$20 annually. The overall elasticity² found in this study, -1.48, is very large relative to empirical estimates. His subsequent dissertation (10) is one of the only known studies to use the 2009 NHTS, pooling it with the 2001 version. While his estimate of the average price-elasticity of demand for miles is over 1 in absolute value with each dataset alone, for the pooled data it is -0.42. The results suggest that a flat-rate VMT fee is neither more nor less regressive than the gas tax, but that a VMT fee would lower the burden on retired people and those in rural areas.

Modeling Vehicle Choice and Usage Sequentially to Control for Endogeneity

It is well established in the literature that in order to obtain an accurate estimate of the response to a change in the cost of driving, it is necessary to model the choice of vehicles as well as vehicle utilization, since each can influence the other (11, 12, 13, 14, 15). The omission of this correction is one of the limitations of most recent studies. The exact method to control for

² Elasticity measures the change, in percentage terms, of a given variable in response to a one-percent change in a related variable. In this case, -1.48 indicates that on average people would reduce the amount of annual miles driven by 1.48% for every 1% change in the price per mile of driving.

endogeneity typically depends on the type of data being used. It is common for studies with aggregate data to utilize 2 Stage Least Squares (2SLS) or 3 Stage Least Squares (3SLS), while those using micro-level data have traditionally utilized some variant of the methods outlined in Dubin & McFadden's seminal paper (16). This section will review literature pertaining to the estimation of vehicle choice and usage with the Dubin-McFadden method, as it is necessary to use micro data to establish welfare impacts.

Mannering and Winston (11) were the first to adapt the Dubin-McFadden model to vehicle choice and usage. They utilized data from the Household Transportation Panel and the National Interim Energy Consumption Survey (NIECS) for 1977-1980 to investigate changes in vehicle ownership and utilization resulting from the 1979 energy crisis, concluding that it would have a small effect on gasoline consumption and vehicle use. Their method included using a multinomial logistic model to estimate the discrete choice of vehicle ownership, utilizing the resulting probabilities in place of variables indicating vehicle characteristics when estimating the vehicle utilization equation.

Train (12) utilized a sequentially estimated nested logit structure to estimate the discrete choice of vehicle type from the 1978 National Transportation Survey. By estimating the relationship between household characteristics and the average operating cost of vehicles in different nests, he was able to add additional information to the discrete choice estimation while avoiding additional bias due to endogeneity that would result from using the actual demand for miles for each household. He corrected for endogeneity of vehicle choice in the continuous estimation of vehicle utilization by using the instrumental variable method rather than the conditional expectation method used in most studies, which entailed creating instruments for per-mile operating costs. He reports an elasticity of about -0.28 for one vehicle households, and an insignificant elasticity for households with two vehicles.

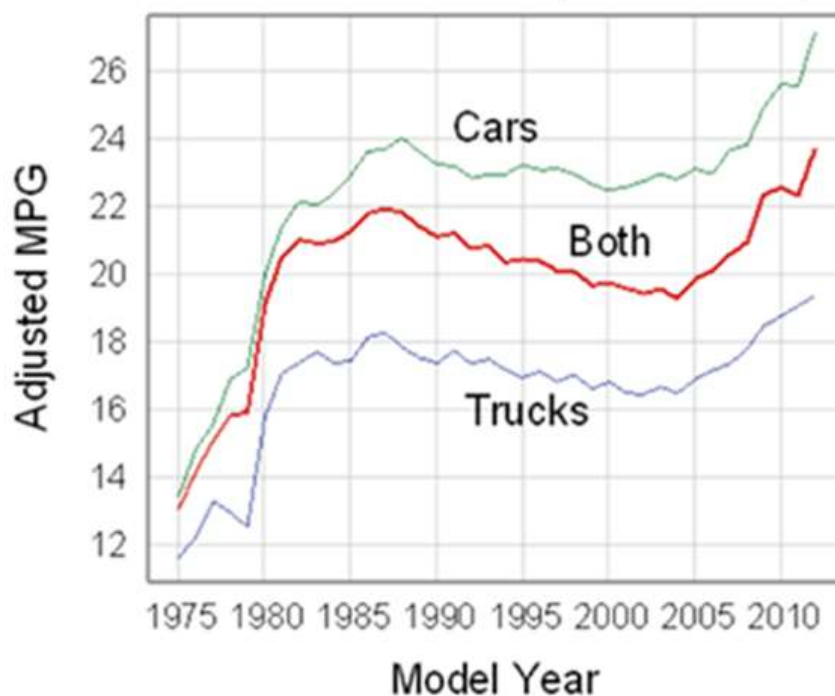
West (13, 14), using data from the 1997 CEX, considers welfare effects of a VMT fee while controlling for endogeneity of vehicle choice resulting from vehicle selection. She makes the important distinction that the results of most studies looking at incidence should be interpreted as the incidence for vehicle owners, and not for the population as a whole, since most datasets do not contain households without vehicles. Following the methodology of Dubin & McFadden (16), she utilizes a conditional expectation correction approach to correct for selection bias (13). The elasticity of VMT with respect to price-per-mile is estimated for each income

quintile, which enables her to calculate the change in consumer surplus and taxes paid for both vehicle owners and the population as a whole. Her results indicate that, of vehicle owners, those in the lowest income decile have a price elasticity of -1.46, with price elasticities decreasing to -.77 for those in the 8th decile. This would seem to indicate that those with lower incomes should be better able to avoid the tax by substituting other travel modes in the long-run, but the overall welfare impact would depend on what activities they had to give up to do so. Her work does not consider any possible feedback effects between VMT and the price per mile. While she compares the equity implications of the gas tax to those of an emissions fee, she does not look at the possibility of a mileage charge replacing the gasoline tax.

A recent dissertation (15) applied the same approach as to the 2001 NHTS dataset, appended with data on vehicle prices and annual service miles of public transportation available in each CMSA/MSA. The main finding is that while the elasticity of demand for miles in low transit areas resembles the pattern found by West (14), the opposite pattern is found for households in high transit areas and for households with vehicles in general. She does not compare the regressivity of a mileage fee to an increase in the per gallon excise tax.

As of now, no known studies have compared the welfare impacts of per mile fees to excise taxes utilizing estimates obtained by applying the Dubin-McFadden 'Conditional Expectation Correction Method' to the most recent 2009 NHTS data. A major limitation of the studies that have explicitly looked at welfare impacts of switching to a VMT fee is that they do not explicitly correct for selection bias. Selection bias is important to consider, as its presence can lead to biased and inconsistent estimates. In addition, the existing literature has had conflicting results with respect to the regressivity of a VMT fee relative to the gas tax (7, 8, 9, 10, 17). It is important to see if these confounding results are due to a structural change or an artifact of estimation procedures. Due to the trends in vehicle fuel efficiency (see Figure 2), it is possible that the distributional effects could be considerably different now than as estimated in studies using older data.

FIGURE 2 Historical Adjusted Fuel Efficiency



Source: United States EPA (18)

DATA

The main sources of data are the 2001 and 2009 National Highway Transportation Survey, which include information on household vehicles, including make, model, and year, as well as household demographic characteristics such as income, household size and number of workers. The dataset also includes variables on miles driven, gasoline cost, and vehicle miles per gallon (MPG).

The NHTS data was appended with data on vehicle operating costs taken from the *Transportation Energy Data Book* (19), which is published annually by the Oak Ridge National Laboratory. This included the annual fixed costs of operating a vehicle based on vehicle year, as well as the per-mile costs of tires and maintenance. Also included in this data was average depreciation based on vehicle year, which was turned into a depreciation rate using the average vehicle price for vehicles sold that year. Since previous studies (13, 15) have noted a close relationship between vehicle prices and annual maintenance, additional data on the price of new vehicles was taken from the 1985-2009 *Ward's Automotive Yearbooks* (20). Ward's publishes these books annually, which contain characteristics of each vehicle on the market in a given year. The simple average of the highest and lowest priced options for each model were calculated and

used to determine annual depreciation for each vehicle based on the average annual depreciation rate for a given year. The vehicle price data was merged with the NHTS data based on the FARS make and model code provided in the dataset after extracting the names from the *2009 NASS (FARS) Vehicle Makes and Models* (21) publication available as part of the user's guide to the 2009 NHTS on the ORNL website. The addition of this vehicle specific data allows for the estimation of a discrete choice model, which is critical to controlling for selection bias.

In order to run regressions on the household level data, some observations had to be removed from the merged dataset. Due to the NHTS having only one category for older vehicles, the analysis was limited to households owning vehicles that were produced no earlier than 1985. Observations which had a vehicle make or model that was not produced in the year provided in the dataset were dropped, as well as observations that did not have recorded values for income, miles driven, or gas cost. In addition, any observation that corresponded to a heavy truck or alternative means of transportation, such as a motorcycle, golf cart, etc., were not included in the regression.

In order to run discrete choice models, household vehicle holdings had to be separated into different categories. In total, 118,021 of the initial 150,147 households remained in the 2009 NHTS after eliminating observations with missing data. Following previous studies (13, 15), trucks, vans, and SUVs were grouped together and classified as trucks. A household with two or less vehicles could have one car, one truck, two cars, two trucks, or a truck and a car, with each classification having three age categories. A household with three or more vehicles could have three of the same class of vehicles or a mixture of cars and trucks. The newest vehicle owned by the household was the bases for the vintage classification for households with less than three vehicles. Table 1 summarizes the age and types of vehicles for 5 different income ranges, as a percentage of all vehicles owned by that income group based on the data. Over 35% of the households in the lowest income category own a single vehicle with a vintage between 1985 and 1999, compared to less than 5% of households with an income over \$100,000. As income increases, households are more likely to own newer vehicles and are more likely to have multiple vehicles.

TABLE 1: Vehicle Holdings by Household Income (Percent)

Vehicle Combo	Year of Newest Vehicle	Household Income					Full Sample
		Less than \$25,000	\$25,000 to \$49,999	\$50,000 to \$74,999	\$75,000 to \$99,999	More than \$100,000	
Car	1985-1999	26.04	10.93	5.21	3.70	2.57	9.49
	2000-2004	16.64	13.14	8.11	6.01	4.70	9.87
	2005-2008	8.49	9.18	7.27	5.42	5.32	7.3
Truck	1985-1999	11.11	5.84	3.44	2.48	1.55	4.83
	2000-2004	7.95	7.92	6.90	5.93	5.16	6.83
	2005-2008	4.13	5.73	5.90	5.37	5.75	5.44
Two Cars	1985-1999	1.46	1.36	1.18	0.99	0.73	1.15
	2000-2004	1.58	2.96	3.51	3.75	3.94	3.16
	2005-2008	1.28	2.80	4.44	5.05	6.64	4.03
Two Trucks	1985-1999	1.18	1.11	0.73	0.56	0.30	0.79
	2000-2004	1.75	3.38	4.20	4.47	2.96	3.33
	2005-2008	1.38	3.67	5.79	7.51	8.06	5.21
Car and Truck	1985-1999	3.15	3.01	2.28	1.54	1.03	2.24
	2000-2004	3.97	7.15	8.62	8.47	7.51	7.17
	2005-2008	3.07	7.06	10.99	13.08	15.76	9.93
Three or More Vehicles		6.88	14.75	21.42	25.68	28.03	19.21
Percent of Sample		16.82	27.50	19.02	14.85	21.81	
Total Observations		19,854	32,456	22,451	17,525	25,735	118,021

Data on state and federal excise taxes were taken from the December 2009 Monthly Motor Fuel Reported by States published by the FHWA Office of Highway Policy Information (22, 23). These were used to calculate tax incidences for each income category and to calculate revenue neutral VMT fees to replace the gasoline tax for each state.

MODEL

The conditional expectation correction method was applied to each dataset to estimate the elasticity of miles with respect to the price-per-mile for each household, which were used to calculate tax incidence and changes in consumer welfare. This approach consists of sequentially estimating vehicle choice and utilization, utilizing the probabilities of a household selecting each vehicle bundle to calculate correction terms to be used as explanatory variables in the estimation of the demand for VMT (12, 13, 16). Barrios (24) showed that the expected probabilities from any Random Utility Maximization (RUM) model can be used to form a selection bias term similar to that found in Dubin & McFadden (16). This corrects for selection bias resulting from

the fact that household miles are only observed for vehicles they have selected to drive, as well as the endogeneity of vehicle combo choice indicators that occurs when unobserved factors influence both choices. Household specific factors were found to interact with the response to a change in the price-per-mile. Including these factors allows for a closer approximation of welfare impacts. State fixed effects are also included to control for unobserved factors within each state that affect driving behavior. More information on the model specifications is available in the appendix.

RESULTS

The results of the regression are shown in Table 2. Variables on the left are variables that interacted with the cost per mile of driving. These variables affect a household's response to a change in the price per mile of driving. Households with more workers, higher incomes, multiple vehicle types, male heads of households, newer vehicles (model years 2005-2009), and households located in the west census region were found to have significantly lower elasticities (in absolute terms) than other households, holding everything else constant. In contrast, households with more trucks or vehicles made before 2005, and households in rural areas with retired persons and/or in the northeast census region were found to have a larger response to a

TABLE 2: Regression for Natural Log of Annual Household Miles Per Vehicle

Variables Interacting With Cost (Per Mile) of Driving	Coefficient (Bootstrapped SE)	Variables Affecting Driving Directly (Independent of Cost Per Mile)	Coefficient (Bootstrapped SE)
ln(cents/mile)	-0.976 (0.031)***	number of drivers	0.045 (0.004)***
ln(cents/mile)*(number of workers)	0.076 (0.014)***	number of workers	0.106 (0.004)***
ln(cents/mile)*sub	0.353 (0.030)***	sub	-0.076 (0.008)***
ln(cents/mile)*trucks	-0.123 (0.027)***	trucks	0.031 (0.005)***
ln(cents/mile)*(employment density)	0.014 (0.009)	ln(employment density)	-0.05 (0.002)***
ln(cents/mile)*rural*retired	-0.129 (0.036)***	ln(employment rate)	0.021 (0.003)***
ln(cents/mile)*old	-0.224 (0.036)***	old	-0.233 (0.014)***
ln(cents/mile)*medium	-0.199 (0.025)***	medium	-0.068 (0.010)***
ln(cents/mile)*ln(income)	0.099 (0.019)***	ln(income)	0.231 (0.004)***
ln(cents/mile)*west	0.126 (0.026)***	education	0.025 (0.002)***
ln(cents/mile)*northeast	-0.06 (0.032)*	rural	0.056 (0.007)***
ln(cents/mile)*male	0.051 (0.021)**	retired	-0.094 (0.007)***
		male	0.097 (0.004)***
		age	-0.007 (0.000)***

Standard errors were bootstrapped with 10000 repetitions to account for the 2 step estimation procedure. Results for selection bias correction and state effects not shown. Meaning of Asterisks: *** means results are significant at 0.01 level or higher. ** means results are significant at 0.05 level. * means results are significant at the 0.1 level.

change in the price per mile. The higher the employment density of the census tract in which a household was located tended to decrease the responsiveness of a household to a price change; however, after accounting for the two-step estimation procedure, this result was no longer significant at traditional levels.

The second column of results in Table 2 show the variables that were found to affect how much people drive, independent of the price-per mile. Households with more drivers, more workers, more trucks and/or vehicles made after 2004, male heads of households, and households located in rural areas and census tracts with a higher employment rate (defined as employment density divided by population density) tend to drive more in a given year. In contrast, households with older vehicles and/or multiple vehicle types, older heads of households or retired persons, and households located in census tracts with higher employment density were found to drive less miles per year.

Elasticities were estimated based on income and other demographics, and are summarized in Table 3. It is evident that households with higher income tend to have a smaller response to price changes, although there is considerable diversity amongst households within each level of income, depending on the age of their newest vehicle and whether they own a truck. The overall elasticity for the sample is -0.81, but households with a single vehicle, particularly those with trucks, tend to have a larger response to a price change. In addition, households with lower incomes tend to have a larger response than average, while households with higher incomes tend to respond less to a price change. The results are consistent with studies using a similar method (13, 25). As in West's estimation, the overall bias corrected for by including the selectivity terms is small but significant. Regression results for the selection bias terms can be found in the appendix. Overall, the elasticities range from -1.67 to -0.01, indicating that some households will be very sensitive to a price change, while others will have little to no response.

TABLE 3: Average Elasticities by Vehicle Holdings and Income

Vehicle Combo	Year of Newest Vehicle	Annual Household Income					<i>Full Sample</i>
		Less than \$25,000	\$25,000 to \$49,999	\$50,000 to \$74,999	\$75,000 to \$99,999	More than \$100,000	
Car	1985-1999	-1.19	-1.04	-0.94	-0.89	-0.85	-1.08
	2000-2004	-1.17	-1.03	-0.94	-0.88	-0.84	-1.02
	2005-2008	-0.96	-0.84	-0.76	-0.69	-0.64	-0.80
Truck	1985-1999	-1.27	-1.11	-1.01	-0.94	-0.91	-1.13
	2000-2004	-1.25	-1.11	-1.03	-0.96	-0.92	-1.07
	2005-2008	-1.06	-0.93	-0.85	-0.79	-0.74	-0.87
Two Cars	1985-1999	-1.16	-1.04	-0.96	-0.92	-0.85	-1.01
	2000-2004	-1.12	-1.01	-0.94	-0.90	-0.85	-0.94
	2005-2008	-0.91	-0.82	-0.75	-0.70	-0.65	-0.73
Two Trucks	1985-1999	-1.12	-0.96	-0.84	-0.80	-0.79	-0.95
	2000-2004	-1.07	-0.94	-0.85	-0.79	-0.77	-0.87
	2005-2008	-0.88	-0.75	-0.66	-0.60	-0.61	-0.66
Car and Truck	1985-1999	-0.95	-0.82	-0.72	-0.68	-0.64	-0.80
	2000-2004	-0.92	-0.80	-0.71	-0.65	-0.61	-0.72
	2005-2008	-0.71	-0.61	-0.53	-0.47	-0.42	-0.50
Three or More Vehicles		-0.85	-0.73	-0.63	-0.56	-0.50	-0.61
Overall Elasticity		-1.11	-0.90	-0.76	-0.68	-0.62	-0.81

Welfare Impacts with Respect to Income and Other Demographic Factors

The welfare impacts were calculated using the elasticities from the sequentially estimated model with the Generalized Dubin-Mcfadden correction based on the latent class logit model. The gasoline tax paid per mile was calculated based on the state and federal excise taxes for each state and the amount of miles driven and gallons of gasoline consumed for each household. After subtracting this from the fuel cost per mile for each household, a VMT fee was applied to each state that would bring in the same amount of revenue at both the state and federal level. In every state, this fee was slightly less than the average tax paid per mile under the current system, which indicates that more miles would be driven overall under the VMT fee.

TABLE 4: Distributional Effects Based on Income

Income	Gas Tax/Income	Revenue Neutral VMT Fee/Income	Change in Consumer Surplus (\$/HH)	Change in CS/Income	% of HH benefitting
\$5,000 to \$24,999	1.377%	1.359%	2.51	0.0158%	60%
\$25,000 to \$49,999	0.742%	0.741%	0.46	0.0017%	58%
\$50,000 to \$74,999	0.589%	0.590%	-0.76	-0.0010%	56%
\$75,000 to \$99,999	0.492%	0.495%	-2.42	-0.0027%	55%
More than \$100,000	0.417%	0.420%	-3.11	-0.0028%	56%

On average, the VMT fee would be slightly less regressive than the current gasoline tax for households with incomes under \$50K. However, the average change in each income category is less than \$5 per year, which is a small fraction of each household's income. While the average is quite small, the range of impacts within each income category is much larger, suggesting that there may be factors other than income that determine the impact on a given household. Nonetheless, the results suggest that the range of impacts would be smaller for households with lower incomes and that a larger proportion of lower income households would benefit from a switch to a VMT fee. This was not the case when looking at earlier datasets, which is likely due to recent trends in fuel efficiency of new vehicles.

Additional analysis was done to determine the impacts of a switch to a VMT fee on retired persons and rural/urban equity. Results are consistent with previous literature, suggesting that retired persons and persons in rural areas would be most likely to benefit. On average, retired persons of all income categories and in both rural and urban areas would benefit. Households of working age, whether in rural or urban areas and regardless of income, would tend to pay slightly more on average. Again, due to considerable diversity amongst households in each of these categories, these averages do not accurately portray the overall range of impacts.

Among households without retirees, almost all households in urban areas would see a change in annual consumer surplus of less than \$300, with most of the lowest income households seeing a change of less than \$200. A significant number of households in rural areas could expect to see impacts between \$300 and \$400 dollars, with some higher income households seeing a change in annual consumer surplus in excess of \$400. Households with retirees would see a significantly smaller range of impacts, particularly in urban areas.

TABLE 5: Average Annual Consumer Surplus Change based on Location and Whether Retired (\$/HH)

Household Income	Rural			Urban		
	Retired	Working	Total	Retired	Working	Total
\$5,000 to \$24,999	7.27	-2.52	3.47	5.38	-2.87	-2.04
\$25,000 to \$49,999	9.80	-4.31	2.74	3.48	-4.85	-0.60
\$50,000 to \$74,999	8.88	-4.94	-0.34	6.86	-5.38	-0.96
\$75,000 to \$99,999	12.44	-2.54	1.07	4.01	-6.74	-3.93
More than \$100,000	3.92	-3.87	-2.28	6.40	-5.76	-3.39

TABLE 6: Range of Change in Consumer Surplus base on Location and Whether Retired

Income	Rural Retired		Rural Working		Urban Retired		Urban Working	
	95% Between (\$/HH)		95% Between (\$/HH)		95% Between (\$/HH)		95% Between (\$/HH)	
	Loss of	Gain of	Loss of	Gain of	Loss of	Gain of	Loss of	Gain of
\$5,000 to \$24,999	-156.31	170.85	-275.84	270.80	-116.76	128.00	-197.11	191.37
\$25,000 to \$49,999	-201.42	221.02	-379.73	371.11	-185.57	193.27	-245.28	235.56
\$50,000 to \$74,999	-244.24	262.00	-373.60	363.72	-162.23	176.89	-252.88	242.12
\$75,000 to \$99,999	-245.94	270.82	-381.23	376.17	-213.95	223.05	-293.88	280.40
More than \$100,000	-317.20	325.04	-422.35	414.61	-212.69	226.75	-302.74	291.22

Those who drive the most miles would tend to pay more on average. These households tend to have higher incomes and own more vehicles, although there are some exceptions. Overall, a VMT fee would be more progressive with respect to miles driven by each household, meaning households who drive in excess of 25K miles per year would tend to pay a larger share of their income in tax relative to households driving less. The annual miles driven by a household, combined with the fuel efficiency of their vehicles are the fundamental determinants of the extent to which they would be better or worse off under a VMT fee system relative to the current gasoline tax. Households with below average fuel economy would benefit from the switch relative to households with above average fuel economy, regardless of other factors. The size of this benefit or loss depends on how much they drive their vehicles. Households that drive more would tend to see a larger change in consumer surplus, particularly if they have a large elasticity.

TABLE 7: Distributional Effects Based on Miles Driven

Total Household Miles (Annual)	Gas Tax/Income	Revenue Neutral VMT Fee/Income	Average Change in Consumer Surplus		Average Number of Vehicles Per Household	95% Between (\$/HH)	
				% of HH benefitting		Loss of	Gain of
Less Than 7,500	0.32%	0.29%	9.08	68%	1.3	-38.62	56.78
7,500 to 14,999	0.58%	0.55%	10.30	57%	1.6	-99.56	120.16
15,000 to 24,999	0.70%	0.69%	6.25	55%	2.0	-174.09	186.59
25,000 or More	1.17%	1.22%	-25.49	49%	2.6	-489.65	438.67

CONCLUSION

Those with more fuel efficient vehicles are likely to be better off under the current system, as they use less fuel per mile. Earlier data, such as the 2001 NHTS, suggest that high income households would benefit the most from a switch to a mileage fee; however, this was likely due to the downward trend in the fuel economy of new vehicles that occurred between 1988 and 2004. Households with higher incomes are much more likely to own new vehicles. This trend is likely to continue, and with recent regulations set to increase the fuel efficiency of newer vehicles drastically over the next decade, this means that these households will be able to further reduce their tax burden unless the system changes.

Households with retired persons and households in rural areas would tend to benefit on average from a switch to a VMT fee structure. The average impacts, however, are not a good representation of the impact on a given household due to diversity in vehicle holdings patterns and miles driven within each category. For example, although rural households would benefit on average, a significant number of rural households would also see the largest impacts, good or bad. Overall, the range of impacts amongst households with retired persons would be smaller, but some could still lose more than \$300 in consumer surplus.

A potential drawback of the present study is that it assumes people will respond to a change in price due to a change in the tax structure the same way they respond to a change in the price of gasoline. A recent paper (30) suggests that people have a much larger response to a change in the gasoline tax than to a change in the price of gasoline, likely due to the saliency of a tax increase. Essentially, people are much more aware of the increase when it comes from a tax

due to media coverage and political debate. It is likely that a change to a mileage fee would be particularly salient, as it would likely require a new form of administration, which could lead to a larger behavioral adjustment. If this is true, the range of impacts could be significantly larger than as stated in this paper.

Another potential issue is that in calculating a VMT fee that would lead to an equivalent amount of revenue it was implicitly assumed that the administration costs of a VMT fee system would be equivalent to the cost of administering the current gasoline tax. If the administration costs were more a higher fee would be required in order to obtain the same amount of revenue. While the overall pattern of impacts between households of different incomes and other demographic factors would likely remain the same as those found in this paper, a higher fee could make it so a larger proportion of households would be worse off. Even if this is the case, it may still be worthwhile to switch to such a system if the long term benefits of stable revenue and improved infrastructure offset these losses. Future research could seek to include administration costs, optimal taxation, and revenue forecasts.

APPENDIX

The model presented below is most similar to the work of West (13), although it has elements from other models which allow for more heterogeneity (7, 9).

In discrete choice models that are consistent with Random Utility Maximization (RUM), it is assumed that the chosen alternative is the one with the highest overall utility; i.e. a household will choose to own the bundle of vehicles (b) for which:

$$U_b > U_j \text{ for all } j \neq b$$

The corresponding probability of choosing a given bundle is:

$$P_b = Prob(U_b > U_j \text{ for all } j \neq b)$$

Since it is not possible to observe the actual utility function of a household, it is necessary to use an approximation based on observable factors, which is known as representative utility (25). The following is the probability of choosing bundle b:

$$P_b = Prob(V_b + \varepsilon > V_j + \varepsilon \text{ for all } j \neq b)$$

The assumption made about the distribution of ε determines which discrete choice model is being used. Logit models utilize the extreme value distribution, which allows for closed form solutions, while probit models utilize the normal distribution and typically involve simulation. Mixed logit models are a generalization of these two types of models in which the error term is a mixing distribution.

Several discrete choice models were estimated and compared in order to find the best fitting model. A mixed logit model can approximate any other discrete choice model, including nested logit (26). This model is desirable because it relaxes the Independence from Irrelevant Alternatives (IIA) hypothesis embodied in multinomial and nested logit models, and is always consistent with utility maximization. In addition, mixed logit models can allow increased heterogeneity in preferences through random coefficients, and can allow these coefficients to be correlated. Traditional mixed logit models assume that random parameters follow a normal distribution, although in practice any mixing distribution can be used to supplement the extreme value distribution that is assumed for the fixed parameters. Latent class models, which are essentially mixed logit models with a discrete mixing distribution, were also estimated, and were found to fit the data much better. Latent class models allow for variation between different unobserved classes, but not within. Consistent Akaike's Information Criterion (CAIC) and

Bayesian Information Criterion (BIC) were used to determine the best fitting model between various specifications of mixed logit and latent class models. These measures take into account the tradeoff between goodness of fit and the number of parameters.

TABLE 1A: Information Criterion Results

Classes	Nparam	LLF	CAIC	BIC
2	36	-290821	582099	582063
3	58	-279347	559430	559372
4	80	-275726	552466	552386
5	102	-278090	557473	557371
6	124	-276540	554652	554528
7	146	-278649	559149	559003
8	168	-277579	557288	557120
9	190	-275865	554138	553948
10	212	-271320	545328	545116
11	234	-275974	554914	554680

Nparam=number of parameters; LLF=value of the likelihood function at convergence; CAIC=Consistent Akaike's Information Criterion; BIC=Bayesian Information Criterion

The probability of selecting a particular bundle in the latent class model can be calculated by taking the weighted average of the traditional logit probability formula with the coefficients estimated for each class:

$$P_{nb} = \sum_{c=1}^C S_c \left(\frac{e^{b'_c x_{nb}}}{\sum_j e^{b'_c x_{nj}}} \right)$$

where the weights (S_c) are the estimated probability household n falls into class c , x_{nb} are observed characteristics of bundle b , x_{nj} are observed characteristics of other bundles, and b'_c is a vector of the estimated coefficients.

It is likely that unobserved factors are correlated with both the choice of vehicle bundle and the demand for miles, which would cause biased estimates due to selectivity. Using the probabilities from the discrete choice model, it is possible to calculate a selection bias correction term for each household of the form (17, 23):

$$\sum_{j \neq b} E \left(\frac{P_{nj} \ln(P_j)}{1 - P_j} \right) - E(\ln(P_b))$$

This term is included as an explanatory variable in the estimation of the demand for VMT by each household. The final equation used for the estimation of demand for miles is:

$$\ln(VMT_b) = \alpha \ln(income) + \gamma \ln(cost/mile) + \gamma \ln(cost/mile) * income \\ + \beta_j \ln(cost/mile) h'_j + \beta_k h'_k + \beta_{state} \\ + \left[\sum_{i \neq b} E \left(\frac{P_i \ln(P_i)}{1 - P_i} \right) - E(\ln(P_b)) \right] + \eta$$

The main results of this regression are available in Table 2 of the main paper. The results for the selectivity correction terms are shown in Table 2A. The only vehicle combo that didn't have any significant selection bias was combo 7, which included two old cars. This would seem to indicate that households driving two cars made before the year 2000 did not select these cars based on some unobserved factors that would also affect their driving.

TABLE 2A: Selectivity Correction Term Results

Selectivity Correction Term	Coefficient (Bootstrapped SE)	Selectivity Correction Term	Coefficient (Bootstrapped SE)
Old Car	0.0019 (0.0005)***	Two Trucks (Old)	-0.0044 (0.0005)***
Med Car	0.0006 (0.0003)*	Two Trucks (Med)	-0.0051 (0.0003)***
New Car	-0.0006 (0.0003)*	Two Trucks (New)	-0.0064 (0.0003)***
Old Truck	-0.0043 (0.0005)***	Car & Truck (Old)	-0.0022 (0.0004)***
Med Truck	-0.0064 (0.0003)***	Car & Truck (Med)	-0.0029 (0.0003)***
New Truck	-0.0059 (0.0002)***	Car & Truck (New)	-0.0038 (0.0002)***
Two Cars (Old)	0.0007 (0.0005)	Three or More (Diff Type)	0.0028 (0.0004)***
Two Cars (Med)	0.0016 (0.0003)***	Three or More (Same Type)	0.0028 (0.0003)***
Two Cars (New)	0.0006 (0.0003)**		

All of the other combos including multiple vehicles show signs of selection bias at the 5% level of significance, with most being significant at the 1% threshold. Of single vehicle households, households owning a car made between 2000 and 2009 show marginal selection bias, as they are significant at the 10% level, while the rest of households show significant selection bias at the 1% threshold. Overall, these results confirm that it is appropriate to correct for selection bias when estimating the elasticity of the demand for miles with respect to the price per mile.

Furthermore, it is possible to understand a little bit about the selection effects present in the main regression. Coefficients that are negative indicate that unobserved factors that affect selection of that combo also lead to higher use of that combo. The largest selection effects are present in households with less than two vehicles owning at least one truck. All of these combos have negative coefficients, and all are highly significant. This indicates that households that buy trucks tend to have reasons to drive these trucks more, which are not otherwise captured in the regression. For example, some households may have jobs, such as in agriculture, which would require them to drive a truck. This would lead to them driving their trucks more than could be explained by income and other demographic variables, and would end up biasing the results of an ordinary least squares (OLS) regression.

Overall, the sequential estimation procedure to correct for selection bias pioneered by Dubin and McFadden (16) seems to lead to slightly lower elasticity estimates than OLS would without controlling for selection bias. The results, with an average elasticity of -0.81 are consistent with previous work utilizing this methodology (13). It should be noted, however, that West's elasticity estimates represented the elasticity of miles driven with respect to total operating costs, which included maintenance and tires. The model utilized in this study estimated this elasticity with respect to fuel cost per mile instead, which is consistent with other studies (28, 29). This doesn't seem to be a contradiction, as the price of gas increased much faster than inflation between the time when the 2009 NHTS and the data used in these studies was collected. The average total operating cost per mile for households with vehicles in West (13) is 10 cents per mile, which, adjusted for inflation, would have been 13.67 cents in 2009. The average price per mile in the 2009 NHTS dataset that is used is 15.55 cents.

REFERENCES

- (1) GAO. (2013). *High-Risk Series - An Update*. Washington, DC: United States Government Accountability Office.
- (2) RITA. (2013). *Table 4-23: Average Fuel Efficiency of U.S. Light Duty Vehicles*. Retrieved from Bureau of Transportation Statistics - Research and Innovative Technology Administration: http://www.rita.dot.gov/bts/sites/rita.dot.gov.bts/files/publications/national_transportation_statistics/html/table_04_23.html
- (3) CBO. (2013). *Statement for the Record - Status of the Highway Trust Fund*. Washington: Congressional Budget Office.
- (4) Schweitzer, L. (2009). *The Empirical Research on the Social Equity of Gas Taxes Emissions Fees, and Congestion Charges*. Transportation Research Board.
- (5) Miller, T. C. (2014). Improving the Efficiency and Equity of Highway Funding and Management - The Role of VMT Charges. *Mercatus Center Working Paper No. 14-04*.
- (6) Parry, I. W., & Small, K. A. (2005). Does Britain or the United States Have the Right Gasoline Tax? *The American Economic Review*, 95(4), 1276-1289.
- (7) Zhang, L., McMullen, B. S., Valluri, D., & Nakahara, K. (2009). Vehicle Mileage Fee on Income and Spatial Equity: Short- and Long-Run Impacts. *Transportation Research Record*(2115), 110-118.
- (8) McMullen, B. S., Zhang, L., & Nakahara, K. (2010). Distributional impacts of changing from a gasoline tax to a vehicle-mile tax for light vehicles: A case study of Oregon. *Transport Policy*(17), 359-366.
- (9) Weatherford, B. A. (2011). Distributional Implications of Replacing the Federal Fuel Tax with Per Mile User Charges. *Transportation Research Record*(2221), 19-26.
- (10) Weatherford, B. A. (2012). Mileage-Based User Fee Winners and Losers: An Analysis of the Distributional Implications of Taxing Vehicle Miles Traveled, With Projections, 2010-2030. (Doctoral Dissertation). *Pardee RAND Graduate School*, 130 Pages.
- (11) Mannering, F., & Winston, C. (1985). A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization. *Rand Journal of Economics*, 16(2), 215-236.
- (12) Train, K. (1986). *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. Cambridge, MA: The MIT Press.
- (13) West, S. E. (2004). Distributional effects of alternative vehicle pollution control policies. *Journal of Public Economics*(88), 735-757.
- (14) West, S. E. (2005). Equity Implications of Vehicle Emissions Taxes. *Journal of Transport Economics and Policy*, 39(Part 1), 1-24.
- (15) Kim, H.-G. (2007). An Analysis of Income Distribution Effects of a Gasoline Tax: Evidence from the U.S. Micro-level Data. (Doctoral Dissertation). *University of Missouri-Columbia*, 75 Pages.
- (16) Dubin, J. A., & McFadden, D. L. (1984). An Econometric Analysis of Residential Electric Appliance Holdings and Consumption. *Econometrica*, 52(2), 345-362.
- (17) Song, S., Morris, G.L., Khan, A., & Tian, Z. (2013). Incidences of Fuel Tax and Vehicle Miles Travelled Fee: An Equity Analysis based on the Revenue-Neutral Principle. *Submitted to Transportation Research Record*.
- (18) US EPA (2012). *Light Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2012*. Publication EPA-420-R-13-001. Transport and Climate Division. United States Environmental Protection Agency.
- (19) Davis, S. C., Diegel, S. W., & Boundy, R. G. (2010). *Transportation Energy Data Book: Edition 29*. Oak Ridge: Oak Ridge National Laboratory.
- (20) Ward's Reports. (1985-2009). *Ward's Automotive Yearbook*. Detroit, MI: Wards Communications.

- (21) FARS. (2009). *2009 NASS (FARS) Vehicle Makes and Models*. Retrieved from NHTS Publications: <http://nhts.ornl.gov/2009/pub/2009FARSMakeModel.pdf>
- (22) OHPI. (2001). *Monthly Motor Fuel Reported by States - December (FHWA-PL-02-003)*. FHWA Office of Highway Policy Information.
- (23) OHPI. (2009). *Monthly Motor Fuel Reported by States - December (FHWA-PL-10-006)*. FHWA Office of Highway Policy Information.
- (24) Barrios, J. (2004). Generalized Sample Selection Bias Under RUM. *Economics Letters*, 129-132.
- (25) Train, K. (2009). *Discrete Choice Methods with Simulation*. Cambridge, MA: Cambridge University Press.
- (26) McFadden, D. & Train, K. (2000). Mixed MNL Models for Discrete Response. *Journal of Applied Econometrics*, 15, 447-470.
- (27) Sevigny, M. (1998). *Taxing Automobile Emissions for Pollution Control*. Northhampton, MA: Edward Elgar Publishing, Ltd.
- (28) Espey, M. (1998). Gasoline Demand Revisited: An International Meta-Analysis of Elasticities. *Energy Economics*, 20, 273-295.
- (29) Goodwin, P., Dargay, J., & Hanly, M. (2004). Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review. *Transport Reviews*, 24(3), 275-292.
- (30) Li, S., Linn, J., & Muehlegger, E. (2012). Gasoline Taxes and Consumer Behavior. *Harvard Kennedy School, Environmental and Natural Resources Program Discussion Paper #2012-08*.